Argonne NATIONAL LABORATORY

ANL/DIS-10-2

A Quick Guide to Wind Power Forecasting: State-of-the-Art 2009

Decision and Information Sciences Division

About Argonne National Laboratory
Argonne is a U.S. Department of Energy laboratory managed by UChicago Argonne, LLC under contract DE-AC02-06CH11357. The Laboratory's main facility is outside Chicago, at 9700 South Cass Avenue, Argonne, Illinois 60439. For information about Argonne and its pioneering science and technology programs, see www.anl.gov.

Availability of This Report
This report is available, at no cost, at http://www.osti.gov/bridge. It is also available on paper to the U.S. Department of Energy and its contractors, for a processing fee, from:

U.S. Department of Energy
Office of Scientific and Technical Information
P.O. Box 62
Oak Ridge, TN 37831-0062
phone (865) 576-8401
fax (865) 576-5728
reports@adonis.osti.gov

ANL/DIS-10-2

A Quick Guide to Wind Power Forecasting: State-of-the-Art 2009

by
C. Monteiro[1], H. Keko[1], R. Bessa[1], V. Miranda[1], A. Botterud[2], J. Wang[2], and G. Conzelmann[2]
[1]Institute for Systems and Computer Engineering of Porto (INESC Porto)
[2]Decision and Information Sciences Division, Argonne National Laboratory, Argonne, Illinois

November 6, 2009

CONTENTS

FIGURES

TABLES

ACKNOWLEDGMENTS

This report has been prepared by Argonne National Laboratory in collaboration with INESC Porto, Portugal. The INESC Porto team acknowledges the assistance of J. Peças Lopes and Manuel Matos in the preparation of this report.

Argonne National Laboratory's work was supported by the U.S. Department of Energy, Office of Energy Efficiency & Renewable Energy through its Wind and Hydropower Technologies Program under contract DE-AC02-06CH11357.

Argonne National Laboratory, November 6, 2009.

This page is intentionally blank.

PURPOSE

This document contains a summary of the main findings from our full report entitled "Wind Power Forecasting: State-of-the-Art 2009" [1]. The aims of this document are to provide guidelines and a quick overview of the current state-of-the-art in wind power forecasting (WPF) and to point out lines of research in the future development of forecasting systems.

This page is intentionally blank.

1 DEFINITIONS AND ABBREVIATIONS IN WIND POWER FORECASTING

1.1 GENERAL DEFINITIONS

We refer to the following entities and terms throughout the Quick Guide.

CAISO: California Independent System Operator

ERCOT: Electric Reliability Council of Texas

Global Numerical Weather Prediction models: are the core of weather forecasting as they perform most of the data assimilation process and produce the initial and boundary conditions used by limited area models.

ISO: Independent System Operator

Limited area models (regional/mesoscale): developed within the research of mesoscale atmospheric processes (e.g., processes with horizontal scales between 1 and a few hundred kilometers [km]). This scale is relevant for many local weather phenomena, from sea breezes to mountain flows and thunderstorms.

MISO: Midwest Independent System Operator

NERC: North American Electric Reliability Corporation

Numerical Weather Prediction (NWP): uses current weather conditions as input into mathematical models of the atmosphere to predict weather variables; the values used most often for wind power prediction are wind speed and direction.

NYISO: New York Independent System Operator

$\boldsymbol{P_{t-k}}$**:** measured power derived from averaging higher-resolution measurements (e.g., 15 minutes [min.]), which can be instantaneous values or energy, depending on the acquisition system.

$\boldsymbol{\widehat{P}_{t+k|t}}$**:** forecasted wind generation made at time instant t for a look-ahead time $t+k$. It is the average power $\boldsymbol{P_{t+k|t}}$ that the wind farm is expected to generate during the considered period of time (e.g., one hour), if operating under an equivalent constant wind.

Persistence model: a naive prediction model, which stipulates that the wind (or wind power) in the next time step will be the same as occurred in the present time step.

PJM: Pennsylvania-Jersey-Maryland Interconnection

Point or spot forecast: single value of the forecasted wind power generation.

Probabilistic forecasts: probability distribution of the forecasted wind power generation for every look-ahead time.

RTO: Regional Transmission Organization

Time horizon: indicates the total length of the forecasting period (e.g., 72 hours [hrs] ahead) in the future, with a specified time resolution.

Time step: the time resolution of the forecasts is denoted by the time step. Usually, for horizons on the order of 24–72 hours, the time step is hourly. Intra-time step (e.g., intra-hourly) variations of power and their impact are not considered.

Other acronyms and abbreviations are defined where they occur throughout the report.

Table 1-1 provides an overview of the time horizon classifications and the potential application of each classification in the operation and planning of power systems, as well as the usefulness for the generation companies.

TABLE 1-1 Wind Power Forecasting Time Horizons

Time Horizons	Generation Companies	Independent System Operator/Transmission System Operator
Very-short–term (up to 9 hrs)	Intraday market Real-time market	Ancillary services management Unit Commitment Economic Dispatch Congestion management
Short-term (up to 72 hrs)	Day-ahead market Maintenance planning of wind farms Wind farm and storage device coordination	Maintenance planning of network lines Congestion management Day-ahead reserve setting Unit Commitment and Economic Dispatch
Medium-term (up to 7 days)	Maintenance planning of wind farms Maintenance planning of conventional generation	Maintenance planning of network lines

1.2 WIND POWER FORECASTING APPROACHES

The advanced wind power forecasting (WPF) methods are generally divided into two main groups:

- **Physical approach:** consists of several submodels, which together deliver the translation from the NWP forecast at a certain grid point and model level, to power forecast at the considered site and at turbine hub height. Every submodel contains the mathematical description of the physical processes relevant to the translation.

- **Statistical approach:** consists of emulating the relation between meteorological predictions, historical measurements, and generation output through statistical models whose parameters have to be estimated from data, without taking any physical phenomena into account. This extrapolation of NWP forecast to power will be referred to in this document as a "wind-to-power (W2P)" model.

There are some WPF systems that combine the two approaches in order to join the advantages of both and thus improve the forecasts. The state-of-the-art nature of these models can be found in numerous publications, such as [1]–[7]. Figure 1-1 depicts the different approaches used for WPF.

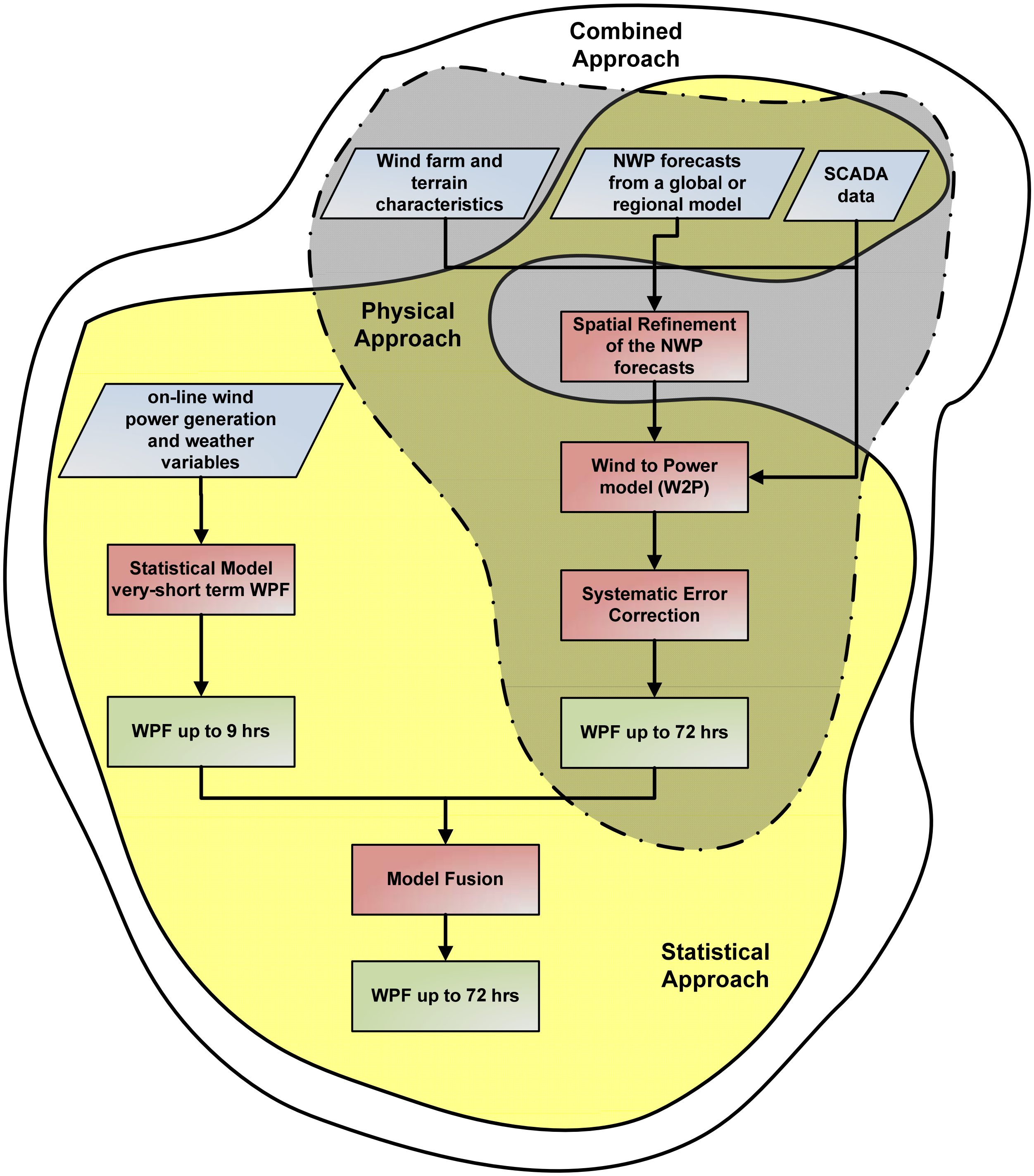


FIGURE 1-1 Different Approaches to WPF

1.3 REGIONAL FORECASTING

Regional/upscaling forecast: to extrapolate the total wind-generated power from predictions carried out for a number of representative (or reference) wind farms, for which Numerical Weather Predictions (NWPs) and/or on-line measurements are made accessible by the forecasting system.

Table 1-2 reports the four approaches in regional (upscaling) forecast.

TABLE 1-2 Regional Forecast Approaches

Approaches	Description
Direct	This approach links the generation and NWP data available from one or more reference wind farms to the regional generation.
Cascaded	This approach is divided into two stages: (1) the power of the reference wind farms is forecasted; (2) the sum is extrapolated to the total regional/national generation.
Cluster or subregions	This approach is divided into three stages: (1) the wind farms are aggregated into clusters; (2) a model is developed for each cluster; (3) the sum of the clusters' generation forecasts provides the total generation for the region.
Combined	This approach is a combination of the aforementioned approaches.

This page is intentionally blank.

2 LITERATURE OVERVIEW OF THE WIND POWER FORECASTING APPROACHES

2.1 VERY-SHORT–TERM WIND POWER FORECASTING

The very-short–term forecasting approach consists of statistical models that are based on the time series approach and includes such models as the Kalman Filters, ARMA, ARX, and Box-Jenkins forecasting methods. These types of models **only take as inputs past values from the forecasted variable** (e.g., wind speed, wind generation). At the same time, **they can also use other explanatory variables** (e.g., wind direction, temperature), which can improve the forecast error. Since these methods are based solely on past production data, **they only outperform the persistence model (reference model) for forecast horizons between 3–6 hours.**

These types of models can be **divided in two groups**: (1) one group forecasts the wind speed and converts to power through an empirical or manufacturer's power curve; and (2) the second group forecasts wind generation directly, without a previous step in which the wind speed is forecasted. Table 2-1 reports the state-of-the-art techniques used in very-short–term WPF.

TABLE 2-1 Research Models for Very-Short–Term WPF

Wind Speed Forecasting	Wind Power Forecasting
Kalman Filter [8], [9]	Fuzzy Time Series [17], [19]
Grey Predictor [10]	Self-exciting Threshold Autoregressive [20]–[22]
Takagi-Sugeno [11]–[14]	Smooth Transition Autoregressive [20]–[22]
Discrete Hilbert Transform [15], [16]	Markov-switching Autoregressive [20]–[22]
Abductive Networks (GMDH) [18]	Adaptive Fuzzy Logic Models [23], [24]
	Adaptive Linear Models [23], [24]
ARIMA time series models [25]–[35]	
Neural Networks [19], [36]–[41]	
Adaptive Neural Fuzzy Inference System [31], [42], [43]	

2.2 SHORT-TERM WIND POWER FORECASTING USING NWP

The literature makes reference to several techniques, and their performance is evaluated in the context of the WPF problem. Generally, these techniques are used to convert the NWP forecasts to wind power: this is the so-called W2P model. Table 2-2 reports the state-of-the-art techniques used in short-term WPF.

TABLE 2-2 Statistical and Computational Methods for Short-Term WPF

Methods
Neural Networks [44]–[50]
Support Vector Machines [44], [45], [50]
Regression Trees with Bagging [44]
Random Forests [44], [50]
Adaptive Neural Fuzzy System [51], [52]
Mixture of Experts [45]
Nearest Neighbor Search [45], [50]
Autoregressive with Exogenous input (ARX) [35]
Locally Recurrent Neural Networks [53], [54]
Local Polynomial Regression [46], [55]
Takagi-Sugeno Fuzzy Inference System [56]
Fuzzy Neural Networks [57]
Autoregressive with Exogenous Input and Multi-timescale Parameter (ARXM) [58]
Bayesian Clustering by Dynamics (BCD) [59]

Table 2-3 summarizes the main conclusions of the short-term WPF.

TABLE 2-3 Main Conclusions of the Short-Term WPF

Combining several statistical models for day-ahead forecasts to decrease the forecast error [44], [46].	Spatial and temporal information from a wide area improves a single wind farm forecast [60].	WPF error can be reduced by using optimization algorithms for feature selection and parameters setting [60].
A transfer coefficient method is proposed in [58] to downscale NWP forecasts, which only takes a few seconds with one computer.	*Sideratos et al.* [61] and *Fan et al.* [59] reported the importance of dividing the dataset into several subsets and fitting a model to each subset.	The authors of [62] showed that combining a few number of NWP forecasts can easily improve the forecast error.
The main trend in learning algorithms is being adaptive in order to deal with data streams and non-stationary processes.	The non-Gaussian error distributions have motivated research to find new cost functions (e.g., error entropy minimization) [47].	The authors of [63] studied the improvement in the initial performance by supplying a “theoretical” wind farm power curve calculated with Wind Atlas Analysis and Application Program or WAsP, particularly for new wind farms.
The authors of [63] demonstrated that stability measures and mesoscale modeling can further improve the physical models.	The use of Kalman Filters to remove systematic errors of NWP wind speed forecasts is valuable [64].	The performance of the models is strongly related to the terrain complexity of the wind farm [65], and the spatial resolution of the NWP forecasts was highly important for WPF.

2.3 REGIONAL FORECASTING

As far as regional forecasting (or upscaling) is concerned, **several publications studied the effects of the number and location of reference wind farms on the expected power output of a whole region**, as well as its error. It is well documented in the literature that, by aggregating several wind farms over a wide area, weakly correlated forecast errors cancel out as a result of statistical effects.

Table 2-4 reports the main conclusions of the regional WPF.

TABLE 2-4 Main Conclusions of Regional Forecasting

When aggregating several wind farms over a wide area, weakly correlated forecast errors cancel out due to statistical smoothing effects [66].	The magnitude of the forecast error strongly depends on the size of the region — the larger the region, the larger the error reduction [67].	Forecasting errors increase with increasing load factor because of increasingly atypical weather events and higher average wind speeds [68].
Siebert et al. [69] showed that increasing the number of wind farms initially decreases the error. However, after reaching a specific number of wind farms, the error started to increase. The additional information provided by an extra farm is outweighed by the additional noise added to the model's input.	*Siebert et al.* [69] stressed the importance of selection of reference wind farms.	The forecast error depends on the location of reference wind farms, and an upscaling based on subregion shows good performance when the normalized capacities of reference wind farms in each subregion are almost the same.
Gastón et al. [70] identified that there is a limit to the reduction of errors by wind farm aggregation. In fact, groups of more than three wind farms do not necessarily result in a significant reduction of the errors.	*Pinson et al.* [71] concluded that the advanced models for time horizons of up to 15 hours gain more from the smoothing effect than persistence. For a time horizon between 1 and 5 hours, persistence is the only model benefiting from smoothing effects.	There is no significant difference in performance between the modeling approaches (direct, cascade, etc.) [72].
Only a few, well-selected explanatory variables are necessary for regional forecast [72].	*Siebert* [72] found that the relation between single wind farm and regional generation is strongly linear.	*Siebert* [72] identified the need to build adaptive regional forecasting models to deal with the non-stationary process.

2.4 OPERATIONAL AND COMMERCIAL WIND POWER FORECASTING SYSTEMS

Table 2-5 provides an overview of all the commercial and operational WPF systems and their main features.

TABLE 2-5 Overview of Operational and Commercial WPF Systems (generally listed in order of appearance of the references cited)

Model	Developer	Approach	Key Features
Prediktor [73]	Risø, Denmark *(http://www.prediktor.dk)*	Physical	This model provides local refinement of the NWP forecasts; it generates wind power curve modeling, including wake effects.
Previento [74]	University Oldenburg/EMSYS, Germany (*http://energymeteo.de)*	Hybrid	The approach is similar to that used in Prediktor but with regional forecasting and uncertainty estimation.
LocalPred/ RegioPred [75]	CENER, Spain	Hybrid	This model performs regional forecasting; was developed especially for complex terrain (micro-scale modeling); and conducts very-short–term forecasting with ARMA models.
WPPT [76]	IMM.DTU/ENFOR, Denmark (*http://www.enfor.eu)*	Statistical	This model provides point and uncertainty forecasts for a single wind farm, for a group of wind farms, or for a wide region. It uses a time-adaptive process to cope with a non-stationary process, and it takes autocorrelation and diurnal variations into account.
Zephyr [78]	Risø and IMM.DTU, Denmark	Hybrid	This model is a combination of the WPPT and Prediktor models; each wind farm is assigned a forecast model assigned according to the available data.
Casandra [78]	University of Castilla-La Mancha/Gamesa, Spain (*http://www.casandraenergy.com)*	Physical	This model features a statistical downloading method that corrects systematic errors on the mesoscale forecasts; employs multivariate regression to estimate the wind farm power curve; and features the automatic update of power curves.

TABLE 2-5 (Cont.)

Model	Developer	Approach	Key Features
AWPPS [79]	ARMINES, France (*http://www.cenerg.cma.fr/prediction)*	Statistical	This model features very-short–term models based on the statistical time-series approach and short-term models based on fuzzy neural networks (NNs). It combines forecasts by an intelligent weighting of very-short and short-term forecasts. The upscaling prediction model is based on dynamic fuzzy neural networks, and it uses cascaded and cluster approaches with reference wind farms. It includes an uncertainty estimation of confidence intervals and an assessment of prediction risk indices based on weather stability.
WPMS [80]	ISET, Germany	Statistical	It calculates the current power for all wind farms by using the measurements of only a few wind farms (on-line monitoring); provides day-ahead and short-term wind power forecasts for single wind farms, control areas, and subregions; and functions as a multi-NWP that combines the forecasts of three different NWP models from different providers or a multi-scheme ensemble weather forecast system (MSEPS) that uses the forecasts of different members of the ensemble.
WEPROG [81]	WEPROG, Germany (*http://www.weprog.com)*	Hybrid	There are two main models: a weather prediction system running every 6 hours and a power prediction system that uses on- and off-line supervisory control and data acquisition (SCADA) measurements. In the first model, a multi-scheme ensemble prediction limited-area NWP model produces 75 different forecasts (ensembles), which forecast uncertainty and improve forecast accuracy.

TABLE 2-5 (Cont.)

Model	Developer	Approach	Key Features
Sipreólico [82]	University Carlos III of Madrid, Spain	Statistical	The model was built to deal with different levels of available data; several adaptive statistical models are used in order to produce a final forecast using an adaptive combination of the alternative predictions. The two main features are: (1) the adaptability to changes in the operation of the wind farms or in the NWP prediction model; (2) easy and fast adaptability for different wind farms; no pre-calibration is required.
GH Forecaster [83]	Garrard Hassan, UK (*http://www.garradhassan.com/)*	Statistical	It uses multi-parameter statistical regression routines to transform global NWP with appropriate geographical resolution and site data (provided by SCADA systems and/or site measurements) into site-specific models; the site-specific models can be any user-defined transformation between NWP and the site.
SOWIE	Eurowind GmbH, Germany (*http://www.eurowind-gmbh.de)*	Physical	This model uses high-resolution, three-dimensional wind and temperature forecasts as inputs, together with a database of all German wind energy turbines; it provides uncertainty estimation and regional forecasting.
EPREV [84]	INESC Porto/INEGI/CEsA/ CGUL, Portugal	Statistical	EPREV combines autoregressive models for very-short–term forecasting with neural networks for short-term forecasting; each wind turbine is modeled individually, thus enabling the on/off plans of each wind turbine to be identified; the system provides uncertainty forecasts.

TABLE 2-5 (Cont.)

Model	Developer	Approach	Key Features
AleaWind	AleaSoft, Spain (*http://www. aleasoft.com)*	Statistical	The model is capable of providing national, regional, or single wind farm forecasts. It is based on AleaSoft's exclusive forecasting model; the parameters of an NN with a SARIMA (or Seasonal Auto‐Regression Integrated Moving Average) structure are estimated on-line.
Scirocco	Aeolis Forecasting Services, Netherlands (*http://www. windknowhow.com)*	Hybrid	The wind power forecast is an output of a model chain with consecutive steps from physical and statistical procedures; the system adapts itself to local geographical circumstances and wind farm characteristics during the first months of operation.
MeteoLógica	MeteoLógica, Spain (*http://www. meteologica.com)*	Physical	The NWP forecasts are downscaled by an advanced statistical downscaling system that uses local meteorological measurements.
eWind [86]	AWS TrueWind Inc., USA (*http://www.meteosimtruewind.com)*	Hybrid	Instead of using a once-and-for-all parameterization for the local effects, such as that used in the Risø approach, this model runs the ForeWind NWP as a mesoscale model using boundary conditions from a regional weather model; several models are used with different initializations in order to create an ensemble of high-resolution NWP prediction. The output from the ensemble, along with the meteorological data, is used to train statistical models to produce forecasts at the meteorological tower sites and correct systematic errors; an "ensemble compositing model" transforms the ensemble of forecasts into a single probabilistic or deterministic forecast. The model provides uncertainty forecast.

TABLE 2-5 (Cont.)

Model	Developer	Approach	Key Features
WindLogics [87]	WindLogics Inc., USA (*http://www.windlogics.com)*	Statistical	This model uses SVM to convert wind speed to generation, and it is retrained every month in order to include new generation and weather data; it uses an ensemble of the National Center for Environmental Prediction (NCEP) Rapid Update Cycle (RUC), North American Model (NAM), and the Global Forecast System (GFS).
PowerSight [88]	3TIER, USA (*http://www.3tiergroup.com)*	Statistical	It provides hourly forecasts for 7 days and 84 hours ahead; the best of 6 different configurations of NWP models (WRF or MM5) is chosen to forecast the weather variables; the power forecast uncertainty is estimated by using quantile regression or conditional on power curve location; a weather forecast ensemble is employed by using a series of NWP simulations, each obtained from different initial conditions or NWP models. The system provides hourly forecasts for a time horizon of up to 10 hours for which historical day-ahead forecasts and weather variables of other sites are used.
Precise Stream	Precision Wind, USA *(http://www.precisionwind.com/)*	Physical	This model is based on meso-microscale atmospheric models (computational fluid dynamics techniques). The main feature is the ability to capture a full 17 km of vertical model depth as well as hundreds of km in the horizontal direction. The model uses three grids with different levels of horizontal resolution to define a large area around the site. The training method is a post-processing step that requires only three months' worth of data. Uncertainty estimation is also provided in the form of maximum and minimum wind generation

TABLE 2-5 (Cont.)

Model	Developer	Approach	Key Features
			values that vary according to current and forecasted weather conditions.
WEFS [85]	AMI Environmental Inc., USA (*http://www.amiace.com)*	Hybrid	In order to account for the local topography and micro-scale effects, the NWP predictions of MM5 or WRF (Weather Research and Forecasting Model) are coupled with a Diagnostic Wind Model developed by AMI; an adaptive statistical model is used to account for the systematic errors without requiring long sampling time and extensive monitoring data.
WindCast	WSI, USA *(http://www.wsi.com/)*	–	WindCast provides hourly wind speed and power forecasts for single wind farms up to seven days ahead. The forecasts can be updated seven times a day.

3 FORECAST UNCERTAINTY

3.1 UNCERTAINTY REPRESENTATION

Recent research has focused on associating uncertainty estimates to point forecasts, taking into account the form of probabilistic forecasts, risk indices, or scenarios of short-term wind power generation.

Probabilistic forecasts [89]–[94]: consist of estimating the future uncertainty of wind power that can be expressed as a probability measure (e.g., quantile).

Risk indices [95], [96]: provide comprehensive information on the expected level of forecast accuracy (the predictability of the atmospheric situation), an a priori warning on expected level of prediction error.

Scenarios of generation [97]–[99]: provide information on the development of the prediction errors through the set of look-ahead times and can also model the spatial and spatial-temporal interdependence of forecast uncertainty.

Table 3-1 summarizes the different types of uncertainty representation in WPF.

Table 3-1 Different Types of Uncertainty Representation

Uncertainty Representation	
Probabilistic	Quantiles Interval Forecasts Probability Mass Function Probability Density Function
Risk Indices	Meteo Risk Index Prediction Risk Index
Scenarios of Generation	Scenarios with temporal dependency Scenarios with spatial/temporal dependency

3.2 UNCERTAINTY ESTIMATION

The wind power forecast uncertainty can be estimated with three different inputs: (1) NWP point forecasts; (2) power output point forecasts obtained by subjecting the NWP point forecast to a W2P model; and (3) an ensemble of NWP forecasts.

Ensemble of NWP forecasts: the main purpose is to try to assimilate the initial error and the forecast uncertainty by applying either the initial perturbation method or the multi-model method.

Table 3-2 summarizes the different approaches to estimating WPF uncertainty depending on the different inputs used.

TABLE 3-2 Different Approaches for Uncertainty Estimation

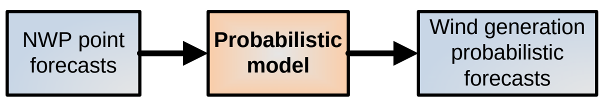
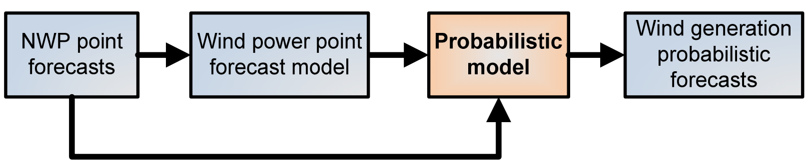
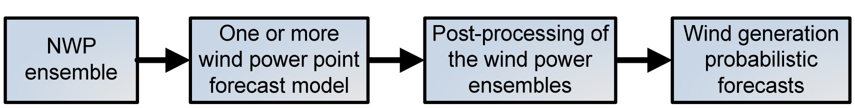
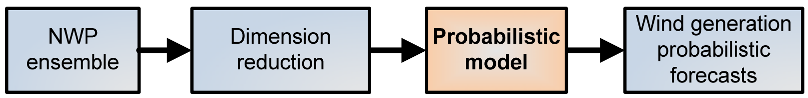
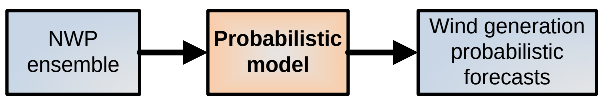
Approaches	Description
	In the ***NWP point forecast approach***, either the NWP forecast error is used as input or the wind power uncertainty is directly computed from the NWP points forecast, e.g., local quantile regression, presented by *Bremnes* [91].
	The ***power output point forecast approach*** consists of forecasting uncertainty based on the WPF errors and NWP point forecasts. The probabilistic model is placed after the model that produces wind power forecasts, e.g., adapted resampling presented by *Pinson* [94].
	In the ***filtering approach***, wind NWP ensembles are converted into power ensembles. For that, each ensemble member uses a single or different point forecasting model. It is also necessary to calibrate the power output ensembles with post-processing methods. This approach can be found in *Nielsen et al.* [77].

TABLE 3-2 (Cont.)

Approaches	Description
	The ***dimension reduction approach*** consists of reducing the input dimensionality and then feeding the reduced inputs to a probabilistic model, e.g., principal component analysis algorithm used by *Bremen et al.* in [100]. The dimension can also be reduced to the ensemble mean and variance.
	The ***direct approach*** consists of feeding the wind ensemble NWPs directly into a probabilistic model; for example, *Juban et al.* in [89] described a quantile regression forest with a random input selection step.

This page is intentionally blank.

4 WIND POWER FORECASTING AND ELECTRICITY MARKET OPERATIONS

4.1 WIND POWER, FORECASTING, AND MARKET OPERATIONS IN U.S. MARKETS

Table 4-1 provides an overview of electricity market operations and the current status of wind power forecasting in five ISO/RTO markets — MISO, NYISO, PJM, ERCOT, and CAISO — in the United States as of May 2009.

TABLE 4-1 Market Operation and Wind Power Forecasting in Five U.S. Electricity Markets

	MISO	NYISO	PJM	ERCOT	CAISO
Peak load	109,157 MW (7/31/2006)	33,939 MW (8/2/2006)	144,644 MW (8/2/2006)	62,339 MW (8/17/2006)	50,270 MW (7/24/2006)
Installed capacity	Ca. 127,000 MW	Ca. 39,000 MW	Ca. 163,000 MW	Ca. 71,000 MW	Ca. 58,000 MW (including imports)
Wind capacity (at end of 2008)	Ca. 4,000 MW	Ca. 1,275 MW	Ca. 2,050 MW	Ca. 8,000 MW	Ca. 2,500 MW
Pricing and congestion management	LMP[a]	LMP	LMP	Zonal (LMP to be introduced)	LMP
Reserve requirements	– Based on NERC standards. – Demand curve for reserves. – Zonal reserve requirements. – Demand can participate in all markets. – Requirements updated daily. – Published two days ahead. – Wind not directly considered.	– Based on NERC standards. – Demand curve for reserves. – Zonal reserve requirements (three zones). – Demand can participate in all markets. – Requirements updated monthly. – Wind not directly considered.	– Based on NERC standards. – Regulation: 1% of peak load (hrs. 5–24), 1% of valley load (hrs. 0–5). – Zonal reserve requirements. – Demand can participate in all markets. – Wind not directly considered.	– Using own requirements, similar to NERC. – System-wide requirements. – Updated monthly. – Wind and forecast error considered for regulation and non-spinning.	– Based on Western Electricity Coordinating Council criteria and NERC standards. – Regional requirements enforced (up to eight regions). – Published two days ahead. – Wind not directly considered.

TABLE 4-1 (Cont.)

	MISO	NYISO	PJM	ERCOT	CAISO
DA[a] market	Energy + regulation, spinning, supplemental reserves co-optimized.	Energy + regulation, spinning, supplemental reserves co-optimized.	Energy + supplemental reserves co-optimized.	No energy but regulation, spinning, supplemental, replacement reserves.	Energy + regulation, spinning, supplemental reserves co-optimized.
RT[a] market	Energy + regulation, spinning, supplemental reserves co-optimized.	Energy + regulation, spinning, supplemental reserves co-optimized.	Energy + regulation, spinning reserves co-optimized.	Energy balancing market.	Energy + regulation, spinning, supplemental reserves co-optimized.
Market timeline	DA offers due: 11:00 a.m. DA results: 4:00 p.m. Re-bidding due: 5:00 p.m. RT offers due: OH[a] – 30 min.	DA offers due: 5:00 a.m. DA results: 11:00 a.m. RT offers due: OH – 75 min.	DA offers due: 12:00 noon DA results: 4:00 p.m. RT offers due: 6:00 p.m. (DA)	DA bids due (reserves): 1:00 p.m./ 4:00 p.m. DA results (reserves): 1.30 p.m./ 6:00 p.m. RT offers due: OH – 60 min.	DA offers due: 10:00 a.m. DA results: 1:00 p.m. RT offers: OH – 75 min.
RT dispatch frequency	5 min.	5 min.	5 min.	15 min.	5 min.
Centralized unit commitment procedure?	Yes. SCUC is used for DA, post-DA, and intra-day, as needed.	Yes. SCUC is used for DA and 75-min. before RT (results 45 min. before RT).	Yes. SCUC is used for DA, post-DA, and intra-day, as needed.	No. Will be introduced with nodal market.	Yes. SCUC is used for DA, HA[a], and for RT operations.
Wind forecasting	In operation since 2008: – 90+ nodes included. – Transmission outage coordination. – Wind impact tool for ramp event impact on flowgates. – Transmission security and peak load analysis. – Input to reliability UC.	In operation since 2008: – DA forecast twice daily (4:00 am, 4:00 pm). – RT forecast every 15 min. – Reliability pass of DA SCUC. – Real-time commitment and dispatch. – Wind plants are required to provide meteorological data to NYISO.	Forecasting system is being introduced in 2009: – Four types of forecasts (short, medium, long, ramp). – Each wind farm is required to provide info from one meteorological tower.	In operation since 2008: – Updated hourly. – 80% exceedance forecast used for DA planning.	Introduced in 2004: – Next hour, next day, extended. – Part of PIRP. – Used in HA market, as PIRP participants must bid forecast. – Wind plants are required to provide meteorological data to ISO.

TABLE 4-1 (Cont.)

	MISO	NYISO	PJM	ERCOT	CAISO
Wind forecasting developments	– Automated procedure for use in system operations. – Required participant provision of DA forecasts.	– Wind plants are required to bid into RT markets (DA optional). – Bids included in RT dispatch to improve efficiency. – Penalties for exceeding base points. – Ramping alert system. – More/better data from plants. – Evaluating needs for operating reserves.	Planned use: – Reliability assessment (DA and RT). – Unit commitment (DA and RT). – Ancillary services (regulation, contingency). – Rules for wind power plant bidding, dispatch, and control being introduced.	– To be fully integrated in DA and RT operations in new nodal design to be introduced at the end of 2010.	– Improving data quality. – Improving forecast quality. – Will integrate forecast into new MRTU market design, including DA operations.
Imbalance settlements for wind power	Most wind settled at RT price. No deviation penalties.	No penalties for deviation from schedule in RT (3,300 MW exempt from penalties).	Wind usually settled at RT price.	Settled at real-time zonal energy price. No deviation penalties.	Deviations netted over month at average price. No deviation penalty (PIRP).
Sources	[101], [109]	[106], [107], [110], [111], [112]	[101], [108], [113], [114]	[101], [103], [104], [115], [116]	[101], [102], [105], [117], [118]

[a] DA = day-ahead, HA = hour-ahead, LMP = locational marginal price, MRTU = Market Redesign and Technology Update, OH = operating hour, PIRP = Participant Intermittent Resource Program, RT = real-time, SCUC = security-constrained unit commitment.

4.2 AREAS FOR IMPROVEMENTS IN U.S. MARKETS – OVERVIEW

The need for wind power forecasting in power system operations is obviously dependent on the amount of wind power capacity in the system. However, given the rapid increase in wind power generation in many areas of the United States, it is quickly becoming important for ISOs/RTOs to efficiently utilize the information provided by advanced wind power forecasting models. The need to revise current operating procedures and integrate wind power forecasting into system operation has also been emphasized by NERC's Integration of Variable Generation Task Force in a recent report [119]. In general, wind power forecasting can potentially provide important information to several of the main procedures involved in power system operations (Figure 4-1). The challenge is to efficiently integrate the information from wind power forecasting, including the uncertainty in the forecast, into the operational procedures from calcuation of reserve requirments, day-ahead commitment and scheduling, and intra-day reliability adjustments, all the way to real-time dispatch.

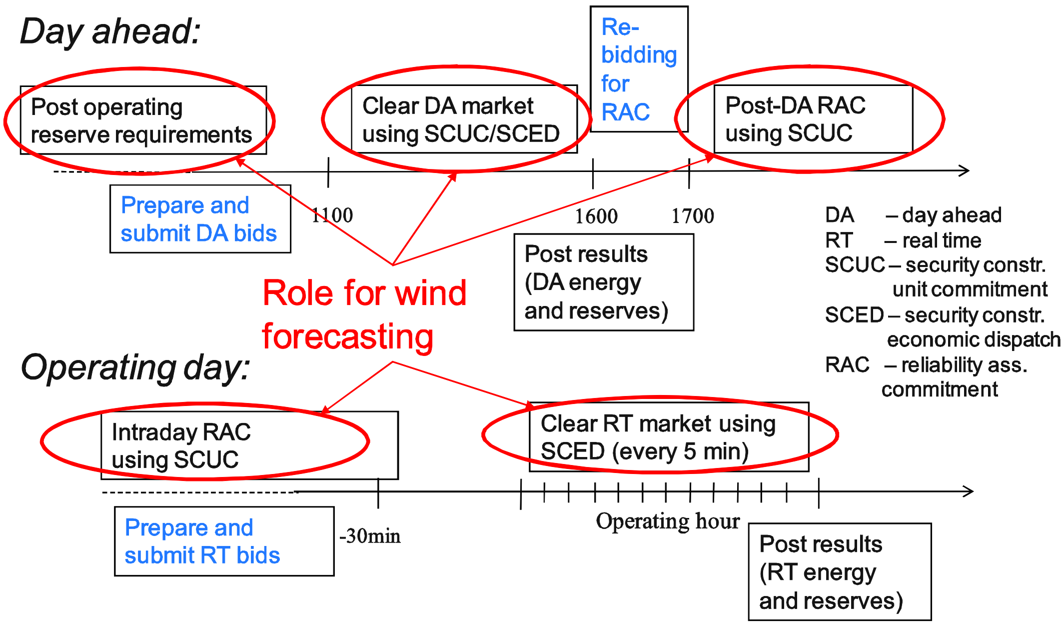


FIGURE 4-1 Role of Wind Power Forecasting in Power System Operations (timeline based on Midwest ISO)

4.3 WIND POWER AND THE UNIT COMMITMENT PROBLEM

Integration of wind power has a broad impact on power system operations, ranging from short-term system operations to long-term planning. The traditional deterministic unit commitment and economic dispatch algorithms currently used in power system operations cannot capture the uncertainty from wind power. In the current unit commitment research on wind power integration [120]–[126], the stochastic unit commitment is discussed repeatedly, and it shows a promising generation scheduling alternative to the deterministic approach. The general idea behind the stochastic formulation is to use scenarios to model uncertainty in wind power output. A generalized stochastic unit commitment formulation is shown in Figure 4-2. The objective is to minimize the expected cost to supply the load. Because of the nonanticipatory constraints, the minimum-on and minimum-off time constraints and capacity limits are enforced for all of the scenarios to obtain a single unit commitment solution. In each scenario, other constraints (such as load balance, ramping up/down, and capacity limits) have to be satisfied.

Objective function:

*Minimize (production cost + load curtailment cost) * probability of each scenario*

Subject to:

For all the scenarios:

Minimum-on and Minimum-off time constraints
Startup and shutdown constraints

For each scenario:

Total thermal generation = load – curtailed load
System reserve requirements
Ramping up/down constraints
Network constraints
Capacity limits

Figure 4-2 Stochastic Security-Constrained Unit Commitment (SCUC) Formulation

Consistent scenario generation is a key to accurately representing the uncertainty and errors in wind power forecasting. A majority of the research so far assumes that the wind power forecasting errors are subject to a normal distribution; however, this may not be a good assumption. Another important aspect of stochastic unit commitment with wind is how an operational policy in terms of reserve requirements should be defined. These issues will be investigated further in this project.

This page is intentionally blank.

5 RELEVANT REFERENCES

5.1 STATE-OF-THE-ART REPORTS

[1] C. Monteiro, R. Bessa, V. Miranda, A. Botterud, J. Wang, G. Conzelmann, "Wind Power Forecasting: State-of-the-Art 2009," Report ANL/DIS-10-1, Argonne National Laboratory, November 2009.

[2] Gregor Giebel, G. Kariniotakis, and R. Brownsword, "State of the Art on Short-term Wind Power Prediction," ANEMOS Deliverable Report D1.1, 2003.

[3] Gregor Giebel, G. Kariniotakis, and R. Brownsword, "The State-of-the-Art in Short-Term Prediction of Wind Power – From a Danish Perspective," in *Proceedings of the 4th International Workshop on Large-Scale Integration of Wind Power and Transmission Networks for Offshore Wind farms*, Billund, Denmark, Oct. 20–21, 2003.

[4] A. Costa, A. Crespo, J. Navarro, G. Lizcano, H. Madsen, and E. Feitosa, "A review on the young history of the wind power short-term prediction," *Renewable and Sustainable Energy Reviews*, vol.12, pp.1725–1744, 2008.

[5] Yuan-Kang Wu and Jing-Shan Hong, "A literature review of wind forecasting technology in the world," in *Proceeding of IEEE Power Tech Conference*, pp. 504–509, Lausanne, Switzerland, July 1–5, 2007.

[6] Lars Landberg, Gregor Giebel, Henrik Aalborg Nielsen, Torben Nielsen, and Henrik Madsen, "Short-term Prediction – An Overview," *Wind Energy*, vol. 6, no. 3, pp. 273–280, 2003.

[7] M. Leia, L. Shiyana, J. Chuanwen, L. Honglinga, and Z. Yana, "A review on the forecasting of wind speed and generated power," *Renewable and Sustainable Energy Reviews*, vol. 13, pp. 915–920, May 2009.

5.2 VERY-SHORT–TERM FORECASTING

[8] E.A. Bossanyi, "Short-Term Wind Prediction Using Kalman Filters," Wind Engineering, vol. 9, no. 1, pp. 1–8, 1985.

[9] H. Vihriälä, P. Ridanpää, R. Perälä, and L. Söderlund, "Control of a variable speed wind turbine with feedforward of aerodynamic torque," in *Proceeding of the European Wind Energy Conference EWEC'99*, pp. 881–884, Nice, France, March 1–5, 1999.

[10] T.H.M. El-Fouly, E.F. El-Saadany, and M.M.A. Salama, "Grey Predictor for Wind Energy Conversion Systems Output Power Prediction," *IEEE Transactions on Power System*, vol. 21, no. 3, pp. 1450–1452, 2006.

[11] I.G. Damousis and P. Dokopoulos, “A fuzzy model expert system for the forecasting of wind speed and power generation in wind farms,” in *Proceedings of the IEEE International Conference on Power Industry Computer Applications PICA 01*, pp. 63–69, 2001.

[12] I.G. Damousis, M.C. Alexiadis, J.B. Theocharis, and P. Dokopoulos, “A fuzzy model for wind speed prediction and power generation in wind farms using spatial correlation,” IEEE Transactions on Energy Conversion, vol. 19, no. 2, pp. 352–361, 2004.

[13] I.J. Ramírez-Rosado and L.A. Fernández-Jiménez, “A new model for short-term wind electric power forecasting,” in *Proceedings of International Conference on Modeling, Identification, and Control*, Innsbruck, Austria, pp. 66–69, 2001.

[14] I.J. Ramírez-Rosado and L.A. Fernández-Jiménez, “An advanced model for short-term forecasting of mean wind speed and wind electric power,” *Control and Intelligent Systems*, vol. 31, no. 1, pp. 21–26, 2004.

[15] S. Alpay, L. Bilir, S. Ozdemirny, and B. Ozerdem, “Wind speed time series characterization by Hilbert transform,” *International Journal of Energy Research*, vol. 30, pp. 359–364, 2006.

[16] Zuojin Zhua and Hongxing Yang, “Discrete Hilbert transformation and its application to estimate the wind speed in Hong Kong,” *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 90, pp. 9–18, 2002.

[17] I.J. Ramírez-Rosado and L.A. Fernández-Jiménez, “Next-day wind farm electric energy generation forecasting using fuzzy time-series,” in *Proceedings of International Conference on Modeling, Identification, and Control*, Innsbruck, Austria, pp. 237–240, 2003.

[18] R.E. Abdel-Aal, M.A. Elhadidy, and S.M. Shaahid, “Modeling and forecasting the mean hourly wind speed time series using GMDH-based abductive networks,” *Renewable Energy*, vol. 34, no. 7, pp. 1686–1699, July 2009.

[19] A. Costa, A. Crespo, and E. Migoya, “First results from a prediction project,” in *Proceeding of the European Wind Energy Conference EWEC’03*, Madrid, Spain, 2003.

[20] P. Pinson, L.E.A. Christensen, H. Madsen, P. Sørensen, M.H. Donovan, and L.E. Jensen, “Regime-switching modelling of the fluctuations of offshore wind generation,” *Journal of Wind Engineering & Industrial Aerodynamics*, vol. 96, no. 12, pp. 2327–2347, 2008.

[21] P. Pinson, H. Madsen, P.E. Sorensen, and N. A. Cutululis, “Adaptive modelling of offshore wind power fluctuations,” in *Proceedings of Nordic Wind Power Conference*, Roskilde, Denmark, 2007.

[22] P. Pinson and H. Madsen, “Adaptive modeling and forecasting of wind power fluctuations with Markov-switching autoregressive models,” *International Journal of Forecasting*, 2009 (submitted).

[23] G. Kariniotakis, E. Nogaret, and G. Stavrakakis, “Advanced Short-Term Forecasting of Wind Power Production,” in *Proceeding of the European Wind Energy Conference EWEC’97*, Ireland, pp. 751–754, October 1997.

[24] G. Kariniotakis, E. Nogaret, A.G. Dutton, J.A. Halliday, and A. Androutsos, “Evaluation of Advanced Wind Power and Load Forecasting Methods for the Optimal Management of Isolated Power Systems,” in *Proceeding of the European Wind Energy Conference EWEC’99*, pp. 1082–1085, Nice, France, March 1–5, 1999.

[25] G.C. Contaxis and J. Kabouris, “Short term scheduling in a wind/diesel autonomous energy system,” IEEE Transactions on Power Systems, vol.6, no. 3, pp. 1161–1167, 1991.

[26] L. Kamal and Y.Z. Jafri, “Time series models to simulate and forecast hourly average wind speed in Quetta,” *Solar Energy*, vol. 61, no. 1, pp. 23–32, 1997.

[27] U. Schlink and G. Tetzlaff, “Wind speed forecasting from 1 to 30 minutes,” *Theoretical and Applied Climatology*, vol. 60, pp. 191–198, 1998.

[28] P. Poggi, M. Muselli, G. Notton, C. Cristofi, and A. Louche, “Forecasting and simulating wind speed in Corsica by using an autoregressive model,” *Energy Conversion and Management*, vol. 14, no. 20, pp. 3177–3196, 2003.

[29] J.L. Torres, A. García, M. de Blas, and A. de Francisco, “Forecast of hourly averages wind speed with ARMA models in Navarre,” *Solar Energy*, vol. 79, no. 1, pp. 65–77, 2005.

[30] C. Tantareanu, “Wind prediction in short-term: a first step for a better wind turbine control,” Nordvestjysk Folkecenter for Vedvarende Energi, October 1992.

[31] A. Sfetsos, “A comparison of various forecasting techniques applied to mean hourly wind speed time series,” *Renewable Energy*, vol. 21, no. 1, pp. 23–35, 2000.

[32] Y.V. Makarov, D.L. Hawkins, E. Leuze, and J. Vidov, “California ISO Wind Generation Forecasting Service Design And Experience,” in *Proceeding of the 2002 AWEA Windpower Conference*, Portland, Oregon, June 2–5, 2002.

[33] M. Milligan, M.N. Schwartz, and Y. Wan, “Statistical Wind Power Forecasting for U.S. Wind Farms,” in Proceedings of the 17th Conference on Probability and Statistics in the Atmospheric Sciences/2004 American Meteorological Society Annual Meeting Seattle, Washington, Jan. 11–15, 2004.

[34] R.G. Kavasseri and K. Seetharaman, “Day-ahead wind speed forecasting using f-ARIMA models,” *Renewable Energy*, vol. 34, no. 5, pp. 1388–1393, May 2009.

[35] Mario J. Duran, Daniel Cros, and Jesus Riquelme, “Short-Term Wind Power Forecast Based on ARX Models,” *Journal of Energy Engineering*, vol. 133, no. 3, pp. 172–180, Sept. 2007.

[36] M.C. Alexiadis, P.S. Dokopoulos, H.S. Sahsamanoglou, and I.M. Manousaridis, “Short-term forecasting of wind speed and related electric power,” *Solar Energy*, vol. 63, no. 1, pp. 61–68, 1998.

[37] M.C. Alexiadis, P.S. Dokopoulos, and H.S. Sahsamanoglou, “Wind speed and power forecasting based on spatial correlation models,” *IEEE Transactions on Energy Conversion*, vol. 14, no. 3, pp. 836–837, 1999.

[38] A. Sfetsos, “A novel approach for the forecasting of mean hourly wind speed time series,” *Renewable Energy*, vol. 27, no. 2, pp. 163–174, 2002.

[39] I. Maqsood, M. Khan, G. Huang, and R. Abdalla, “Application of soft computing models to hourly weather analysis in southern Saskatchewan, Canada,” *Engineering Applications of Artificial Intelligence*, vol. 18, no. 1, pp. 115–125, 2005.

[40] E. Cadenas and W. Rivera, “Short term wind speed forecasting in La Venta, Oaxaca, México, using artificial neural networks,” *Renewable Energy*, vol. 34, no. 1, pp. 274-278, Jan. 2009.

[41] A. Kusiak, H.-Y. Zheng, and Z. Song, "Short-Term Prediction of Wind Farm Power: A Data-Mining Approach," *IEEE Transactions on Energy Conversion*, vol. 24, no. 1, pp. 125–136, 2009.

[42] C.W. Potter and M. Negnevistky, “Very short-term wind forecasting for Tasmanian power generation,” *IEEE Transactions on Power Systems*, vol. 21, no. 2, pp. 965–972, 2006.

[43] Laura Frías, Martín Gastón, and Ignacio Martí, “A new model for wind energy forecasting focused in the intra-daily markets,” poster session of the European Wind Energy Conference EWEC’07, Milan, Italy, 2007.

5.3 SHORT-TERM WIND POWER FORECASTING

[44] Lionel Fugon, Jérémie Juban, and G. Kariniotakis, “Data mining for Wind Power Forecasting,” in *Proceeding of the European Wind Energy Conference EWEC’08*, Brussels, Belgium, April 2008.

[45] R. Jursa, "Wind power prediction with different artificial intelligence models," in *Proceeding of the European Wind Energy Conference EWEC'07*, Milan, Italy, May 2007.

[46] Ismael Sanchez, "Short-term prediction of wind energy production," *International Journal of Forecasting*, vol. 22, no. 1, pp. 43–56, 2006.

[47] R. Bessa, V. Miranda, and J. Gama, "Entropy and Correntropy against Minimum Square Error in Off-Line and On-Line 3-day ahead Wind Power Forecasting," *IEEE Transactions on Power Systems* (paper in revision), 2009.

[48] R. Bessa, V. Miranda, and J. Gama, "Wind Power Forecasting With Entropy-Based Criteria Algorithms," in *Proceedings of International Conference on Probabilistic Methods Applied to Power Systems, PMAPS 2008,* Puerto Rico, May 2008.

[49] S. Salcedo-Sanza, A.M. Pérez-Bellidoa, E.G. Ortiz-García, A. Portilla-Figueras, L. Prieto, and Daniel Paredes, "Hybridizing the fifth generation mesoscale model with artificial neural networks for short-term wind speed prediction," *Renewable Energy*, vol. 34, no. 6, pp. 1451–1457, June 2009.

[50] A. Kusiak, H.-Y. Zheng, and Z. Song, "Wind Farm Power Prediction: A Data-Mining Approach," Wind Energy, vol. 12, no. 3, pp. 275–293, 2009.

[51] M. Negnevitsky, S. Santoso, and N. Hatziargyriou, "Data mining and analysis techniques in wind power system applications: abridged," in *Proceedings of the IEEE Power Engineering Society General Meeting*, 2006.

[52] M. Negnevitsky, P. Johnson, and S. Santoso, "Short term Wind Power Forecasting using hybrid intelligent systems," in *Proceedings of the IEEE Power Engineering Society General Meeting*, pp. 1–4, June 24–28, 2007.

[53] T.G. Barbounis and J.B. Theocharis, "Long-term wind speed and power forecasting using local recurrent neural network models," *IEEE Transactions on Energy Conversion*, vol. 21, no. 1, pp. 273–284, 2006.

[54] T.G. Barbounis and J.B. Theocharis, "Locally recurrent neural networks for long-term wind speed and power prediction," *Neurocomputing*, vol. 69, pp. 466–496, 2006.

[55] P. Pinson, Henrik Aa. Nielsen, and H. Madsen, "Robust Estimation of Time-varying Coefficient Functions – Application to the Modeling of Wind Power Production," Technical Report of the Project Intelligent wind power prediction systems, DTU, Lyngby, Denmark, March 2007.

[56] V. Miranda, C. Cerqueira, and C. Monteiro, “Training a FIS with EPSO under an Entropy Criterion for Wind Power prediction,” in *Proceedings of International Conference on Probabilistic Methods Applied to Power Systems*, PMAPS 2006, Stockholm, Sweden, June 11–15, 2006.

[57] P. Pinson and G. Kariniotakis, “Wind Power Forecasting using fuzzy neural networks enhanced with on-line prediction risk assessment,” in *Proceedings of the IEEE Power Tech Conference*, Bologna, Italy, vol. 2, pp. 23–26, June 2003.

[58] A. Yamaguchi, T. Ishihara, K. Sakai, T. Ogawa, and Y. Fujino, “A Physical-Statistical Approach for the Regional Wind Power Forecasting,” in *Proceeding of the European Wind Energy Conference EWEC’07*, Milan, Italy, 2007.

[59] Shu Fan, James R. Liao, Ryuichi Yokoyama, and Luonan Chen, “Forecasting the Wind Generation Using A Two-stage Hybrid Network Based on Meteorological Information,” *Information and Communication Eng.*, Osaka Sangyo University, 2006.

[60] René Jursa and Kurt Rohrig, “Short-term Wind Power Forecasting using evolutionary algorithms for the automated specification of artificial intelligence models,” *International Journal of Forecasting*, vol. 24, pp. 694–709, 2008.

[61] George Sideratos and Nikos D. Hatziargyriou, “An Advanced Statistical Method for Wind Power Forecasting,” IEEE Transactions on Power Systems, vol. 22, no. 1, February 2007.

[62] H.A. Nielsen, T.S. Nielsen, H. Madsen, M.J.S.I. Pindado, and I. Marti, “Optimal Combination of Wind Power Forecasts,” *Wind Energy*, vol. 10, no. 5, pp. 471–482, July 19, 2007.

[63] H.A. Nielsen, P. Pinson, L.E. Christiansen, T.S. Nielsen, H. Madsen, J. Badger, G. Giebel, and H.F. Ravn, “Improvement and automation of tools for short term Wind Power Forecasting,” in *Proceeding of the European Wind Energy Conference EWEC’07*, Milan, Italy, 2007.

[64] P. Louka, G. Galanis, N. Siebert, G. Kariniotakis, P. Katsafados, G. Kallos, and I. Pytharoulis, “Improvements in wind speed forecasts for wind power prediction purposes using Kalman filtering,” *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 96, no. 12, pp. 2348–2362, Dec. 2008.

[65] G. Kariniotakis, et al., “Next Generation Short-term Forecasting of Wind Power – Overview of the ANEMOS Project,” in *Proceeding of the European Wind Energy Conference EWEC’06*, Athens, Greece, 2006.

5.4 REGIONAL FORECASTING

[66] U. Focken, M. Lange, and H.-P. Waldl, “Reduction of Wind Power Production Error by Spatial Smoothing Effects,” in *Proceeding of the European Wind Energy Conference EWEC’01*, pp. 822–825, Copenhagen, Denmark, June 2–6, 2001.

[67] U. Focken, M. Lange, K. Mönnich, H.-P. Waldl, H.G. Beyer, and A. Luig, “Short-term prediction of the aggregated power output of wind farms – a statistical analysis of the reduction of the prediction error by spatial smoothing effects,” *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 90, no. 3, pp. 139–249, March 2002.

[68] S. Lang, J. Möhrlen, J. Jørgensen, B.O. Gallachóir, and E. McKeogh, “Application of a Multi-Scheme Ensemble Prediction System for Wind Power Forecasting in Ireland and comparison with validation results from Denmark and Germany,” in *Proceeding of the European Wind Energy Conference EWEC’06*, Athens, Greece, 2006.

[69] N. Siebert and G. Kariniotakis, “Reference wind farm selection for regional wind power prediction models,” in *Proceeding of the European Wind Energy Conference EWEC’06*, Athens, Greece, 2006.

[70] Martín Gastón, Laura Frías, and Ignacio Martí, “Exploring the limits of wind farm grouping for prediction error compensation,” in *Proceeding of the European Wind Energy Conference EWEC’06*, Athens, Greece, 2006.

[71] P. Pinson, N. Siebert, and G. Kariniotakis, “Forecasting of Regional Wind Generation by a Dynamic Fuzzy-Neural Networks Based Upscaling Approach,” in *Proceeding of the European Wind Energy Conference EWEC’03*, Madrid, Spain, June 16–19, 2003.

[72] N. Siebert, “Development of methods for regional Wind Power Forecasting,” Ph.D. dissertation, CEP – Centre Energétique et Procédés, ENSMP, 2008.

5.5 OPERATIONAL AND COMMERCIAL WIND POWER FORECASTING SYSTEMS

[73] L. Landberg, “Short-term Prediction of Local Wind Conditions,” Ph.D. dissertation, Risø National Laboratory, Roskilde, Denmark 1994.

[74] U. Focken, M. Lange, and H.P. Waldl, “Previento - A Wind Power Prediction System with an Innovative Upscaling Algorithm,” in *Proceeding of the European Wind Energy Conference EWEC’01*, Copenhagen, Denmark, pp. 826–829, June 2–6, 2001.

[75] I. Marti, D. Cabezón, J. Villanueva, M.J. Sanisidro, Y. Loureiro, E. Cantero, and J. Sanz, “LocalPred and RegioPred. Advanced tools for wind energy prediction in complex terrain,” in *Proceeding of the European Wind Energy Conference EWEC’03*, Madrid, Spain, June 16–19, 2003.

[76] T.S. Nielsen, L. Landberg, and G. Giebel, “Prediction of Regional Wind Power,” Poster Presentation on the Global Windpower Conference, Paris, France, April 2–5, 2002.

[77] H.A. Nielsen, T.S. Nielsen, H. Madsen, G. Giebel, J. Badger, L. Landberg, K. Sattler, L. Voulund, and J. Tofting, “From wind ensembles to probabilistic information about future wind power production – results from an actual application,” in *Proceedings of International Conference on Probabilistic Methods Applied to Power Systems*, PMAPS 2006, pp.1–8, June 11–15, 2006.

[78] G. Giebel, L. Landberg, T.S. Nielsen, and H. Madsen, “The Zephyr Project – The Next Generation Prediction System,” in Poster Presentation on the Global Windpower Conference and Exhibition, Paris, France, April 2–5, 2002.

[79] G. Kariniotakis and D. Mayer, “An Advanced On-Line Wind Resource Prediction System for the Optimal Management of Wind farms,” in *Proceedings of the 3rd MED POWER conference 2002*, Athens, Greece, November 4–6, 2002.

[80] B. Ernst, K. Rohrig, H. Regber, and P. Schorn, “Managing 3000 MW Wind Power in a Transmission System Operation Center,” in *Proceeding of the European Wind Energy Conference EWEC’01*, pp. 890–893, Copenhagen, Denmark, June 2–6, 2001.

[81] S. Lang, J. Möhrlen, J. Jørgensen, B.O. Gallachóir, and E. McKeogh, “Aggregate forecasting of wind generation on the Irish grid using a multi-scheme ensemble prediction system,” in *Proceedings of the 2nd Conference of Renewable Energy in Maritime Island Climates*, Dublin, Ireland, April 2006.

[82] I. Sánchez, J. Usaola, O. Ravelo, C. Velasco, J. Domínguez, M.G. Lobo, G. González, and F. Soto, “SIPREÓLICO – A Wind Power Prediction System Based on Flexible Combination of Dynamic Models. Application to the Spanish Power System,” Poster on the World Wind Energy Conference in Berlin, Germany, June 2002.

[83] J. Parkes and A. Tindal, “Forecasting short term wind farm production in complex terrain,” in *Proceeding of the European Wind Energy Conference EWEC’04*, London, U.K., Nov. 2004.

[84] A. Rodrigues, J. A. Peças Lopes, P. Miranda, L. Palma, C. Monteiro, R. Bessa, J. Sousa, C. Rodrigues, and J. Matos, “EPREV – A Wind Power Forecasting Tool for Portugal,” in *Proceeding of the European Wind Energy Conference EWEC’07*, Milan, Italy, 2007.

[85] E. McCarthy, R. Nierenberg, L. Landberg, J. Zack, and K. Tran, “Texas Wind Energy Forecasting System Development and Testing. Phase 1: Initial Testing,” Technical Report, December 2003.

[86] B. Bailey, M.C. Brower, and J. Zack, “Short-Term Wind Forecasting,” in *Proceeding of the European Wind Energy Conference EWEC’99*, pp. 1062–1065, Nice, France, March 1–5, 1999.

[87] Renewable Energy Research and Development Project – Final Report, Oct. 6, 2008.

[88] Pascal Storck, "Wind Energy Forecasting: The State of the Art & Future Possibilities," Presentation at UWIG Fall Technical Workshop Wind Integration: Focus on the Value of Wind Forecasting, Sacramento, California, Nov. 7–9, 2005.

5.6 UNCERTAINTY IN WIND POWER FORECASTING

[89] J. Juban, L. Fugon, and G. Kariniotakis, "Uncertainty Estimation of Wind Power Forecasts," in *Proceeding of the European Wind Energy Conference EWEC'08*, Brussels, Belgium, March 31–April 03, 2008.

[90] P. Pinson, H. Aa. Nielsen, H. Madsen, M. Lange, and G. Kariniotakis, "Methods for the estimation of the uncertainty of wind power forecasts," ANEMOS project deliverable report D3.1b, Informatics and Mathematical Modelling, Technical University of Denmark, March 2007.

[91] John B. Bremnes, "Probabilistic wind power forecasts using local quantile regression," *Wind Energy*, vol. 7, no. 1, pp. 47–54, 2004.

[92] J. Juban, L. Fugon and George Kariniotakis "Probabilistic short-term wind power forecasting based on kernel density estimators," in *Proceeding of the European Wind Energy Conference EWEC'07*, Milan, Italy, 2007.

[93] H. Bludszuweit, J.A. Dominguez-Navarro, and A. Llombart, "Statistical Analysis of Wind Power Forecast Error," *IEEE Transactions on Power Systems*, vol. 23, no. 3, pp. 983–991, Aug. 2008.

[94] P. Pinson, "Estimation of the uncertainty in wind power forecasting," Ph.D. dissertation, Ecole des Mines de Paris, Paris, France, 2006.

[95] P. Pinson and G. Kariniotakis, "On-line assessment of prediction risk for wind power production forecasts," Wind Energy, vol. 7, no. 2, pp. 119–132, 2004.

[96] P. Pinson, H.Aa. Nielsen, H. Madsen, and G. Kariniotakis, "Skill forecasting from ensemble predictions of wind power," *Applied Energy*, 2009 (in press).

[97] P. Pinson, G. Papaefthymiou, B. Klockl, H.Aa. Nielsen, and H. Madsen "From probabilistic forecasts to statistical scenarios of short-term wind power production," *Wind Energy*, vol. 12, no. 1, pp. 51–62, 2009.

[98] G. Papaefthymiou and P. Pinson, "Modeling of spatial dependence in wind power forecast uncertainty," presented at International Conference on Probabilistic Methods Applied to Power Systems, PMAPS 2008, Puerto Rico, May 2008 (invited oral presentation).

[99] P. Pinson and G. Papaefthymiou, "Spatio-temporal scenario forecasts of wind generation," 2009 (working paper).

[100] L. von Bremen, R. Hagedorn, and T. Peroliagis, "Towards probabilistic wind power forecasting based on ensemble prediction techniques," presentation to the 7th European Meteorological Society Annual Meeting, October 2007.

5.7 WIND POWER AND FORECASTING IN U.S. MARKETS

[101] E. DeMeo, K. Porter, and C. Smith, "Wind Power and Electricity Markets," Utility Wind Integration Group, Sept. 2007. Available at: http://www.uwig.org/windinmarketstable Sep07.pdf.

[102] J. Blatchford, "Wind Energy Forecasting 101," presentation to PJM conference, May 15–16, 2008.

[103] ERCOT (Electric Reliability Council of Texas), "ERCOT Methodologies for Determining Ancillary Service Requirements," ERCOT, February 2009. Available at: http://www.ercot.com/mktinfo/services/.

[104] D. Maggio, "Integrating Wind Forecasting into Market Operation – ERCOT," presentation to the Wind Forecasting Workshop, Utility Wind Integration Group (UWIG), Phoenix, Arizona, Feb. 2009.

[105] C. Loutan and D. Hawkins, "Integration of Renewable Resources: Transmission and Operating Issues and Recommendations for Integrating Renewable Resources on the California ISO-controlled Grid," Report California ISO, Nov. 2007.

[106] R. Gonzales, R. Mukerji, M. Swider, D. Allen, R. Pike, D. Edelson, E. Nelson, and J. Adams, "Integration of Wind into System Dispatch," New York ISO White Paper, Oct. 2008. Available at: http://ww.nyiso.com/public/webdocs/documents/white_papers/ wind_management_whitepaper_11202008.pdf.

[107] M. Swider, "Integrating Wind Forecasting and Bids into Market Operations," presentation at the Wind Forecasting Workshop, Utility Wind Integration Group (UWIG), Phoenix, Arizona, Feb. 2009.

[108] PJM (Pennsylvania-Jersey-Maryland Interconnection), "Wind Generation Operational Considerations," PJM presentation, May 2009. Available at: http://www.pjm.com/~/ media/committees-groups/working-groups/irwg/20090527/20090527-item-03d-wind-dispatching-training.ashx.

[109] M. McMullen, "Integrating Wind Forecasting into Market Operation," presentation at the Wind Forecasting Workshop, Utility Wind Integration Group (UWIG), Phoenix, Arizona, Feb. 2009.

[110] NYISO (New York Independent System Operator), "Market Participants User's Guide," New York ISO, Nov. 2008. Available at: http://www.nyiso.com/public/documents/guides/index.jsp.

[111] NYISO, "Ancillary Services Manual," New York ISO, Sept. 2008. Available at: http://www.nyiso.com/public/webdocs/documents/manuals/operations/ancserv.pdf.

[112] D. Edelson, "Wind Forecasting at the NYISO," presentation at the Wind Forecasting Workshop, Utility Wind Integration Group (UWIG), St. Paul, Minnesota, Feb. 2008.

[113] S. Patil, "Wind Power Forecasting Process Development," presentation at the Spring Technical Workshop and Annual Meeting, Utility Wind Integration Group (UWIG), Philadelphia, Pennsylvania, April 2009.

[114] PJM, "PJM Manual 11: Scheduling Operations," PJM, Jan. 2009. Available at: http://www.pjm.com/documents/manuals.aspx.

[115] ERCOT, "ERCOT Wholesale Market Operations: Module 2," ERCOT Presentation, January 2009. Available at: http://www.ercot.com/services/training/Wholesale_Basics.

[116] ERCOT, "ERCOT Operating Guides. Section 2: System Operation. ERCOT Control Area Authority Operation," ERCOT, March 1, 2009. Available at: http://www.ercot.com/mktrules/guides/operating/.

[117] CAISO (California Independent System Operator), "Business Practice Manual for Market Operations," California ISO, March 23, 2009. Available at: http://www.caiso.com/17ba/17baa8bc1ce20.html.

[118] Y.V. Makarov, C. Loutan, J. Ma, and P. de Mello, "Operational Impacts of Wind Generation on California Power Systems," IEEE Transactions on Power Systems, vol. 24, no. 2, pp. 1039–1050, 2009.

5.8 WIND POWER AND THE UNIT COMMITMENT PROBLEM

[119] NERC (North American Electric Reliability Corporation), "Accommodating High Levels of Variable Generation," Special Report, April 2009. Available at: http://www.nerc.com/news_pr.php?npr=283.

[120] R. Barth, H. Brand, P. Meibom, and C. Weber, "A stochastic unit commitment model for the evaluation of the impacts of the integration of large amounts of wind power," in *Proc. of the 9th Int. Conf. Probabilistic Methods Applied to Power Systems*, Stockholm, Sweden, 2006.

[121] Wind Power Integration in Liberalised Electricity Markets (Wilmar) Project. Available at: http://www.wilmar.risoe.dk.

[122] A. Tuohy, P. Meibom, E. Denny, and M. O'Malley, "Unit Commitment for Systems With Significant Wind Penetration," *IEEE Transactions on Power Systems*, vol. 24, no. 2, pp. 592–601, 2009.

[123] A. Tuohy, E. Denny, and M. O'Malley, "Rolling Unit Commitment for Systems with Significant Installed Wind Capacity," 2007 IEEE Power Tech, pp. 1380–1385, July 1–5, Lausanne, Switzerland, 2007.

[124] A. Tuohy, P. Meibom, and M. O'Malley, "Benefits of stochastic scheduling for power systems with significant installed wind power," in *Proc. 10th Int. Conf. Probabilistic Methods Applied to Power Systems (PMAPS)*, Mayagüez, Puerto Rico, 2008.

[125] F. Bouffard and F. Galiana, "Stochastic security for operations planning with significant wind power generation," *IEEE Transactions on Power Systems*, vol. 23, no. 2, pp. 306–316, 2008.

[126] P.A. Ruiz, C.R. Philbrick, E. Zak, K.W. Cheung, and P.W. Sauer, "Uncertainty Management in the Unit Commitment Problem," *IEEE Transactions on Power Systems*, vol. 24, no.2, pp. 642–651, 2009.

Decision and Information Sciences Division
Argonne National Laboratory
9700 South Cass Avenue, Bldg. 900
Argonne, IL 60439-4867

www.anl.gov

Argonne National Laboratory is a U.S. Department of Energy
laboratory managed by UChicago Argonne, LLC